Low-Cost Textile Myoelectric Control of Knee-Ankle-Foot-Orthosis

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Abstract— **The poorest populations in the world have the highest prevalence of lower limb disabilities, and lack of access to healthcare prevents many from lifting themselves out of poverty. This is particularly true for the large population of poliomyelitis-affected inhabitants of India, whose quality of life would benefit substantially from the provision of affordable, yet modern, dynamic knee-ankle-foot orthoses to assist in ambulation. To this end, this paper reports a study into the use of a low-cost, textile-based sensor interface for the myoelectric control of lower limb orthoses in restoring gait function. It reports experiments examining the accuracy with which gait events in the healthy limb (*e.g.,* heel strike, toe-off) can be detected through the textile interface, with a view to triggering discrete control modes of a smart orthosis (*i.e.,* knee lock and release) to support the atrophied limb during walking. Results show that prediction accuracy through the proposed interface ($\sim 70\%$) approaches that of more traditional medical-grade sensors, despite its substantially lower cost.**

I. Introduction

One billion people globally have a disability, and 80% of them live in developing countries [1]. People with disabilities (PwDs) are over-represented amongst the persistently poor, and are less likely than others to be able to move themselves out of poverty [2]. In India specifically, around 19 million people are estimated to have disabilities, of which around 10.3 million people have a locomotive disability [3].

Knee-ankle-foot orthoses (KAFOs) are commonly used to assist patients with gait dysfunction and allow them to recover mobility and independence. Not all people with a lower limb disability are prescribed a KAFO, and there is lack of data showing exact number of users in India. However, the International Committee of the Red Cross estimates that there are more than 10 million people in India in need of a KAFO [4]. Polio survivors, especially, are in need because their lower limb muscles are usually too weak to be able to support their body weight.

In less economically developed countries, passive-KAFOs—essentially, rudimentary leg-braces that allow the knee joint to be manually locked—are the most commonly used. However, these devices are the bare minimum for enabling locomotion, and healthy gait is not restored. In developed countries, electromechanical KAFOs, or stance-control-KAFOs, allow for knee flexion during the swing phase, along with stance phase knee stability. These devices can often be sensorised, to provide more refined control, enabling patients to, for example, descend slopes and stairs and walk on uneven terrain [5]. However, the high cost of such devices limits their accessibility.

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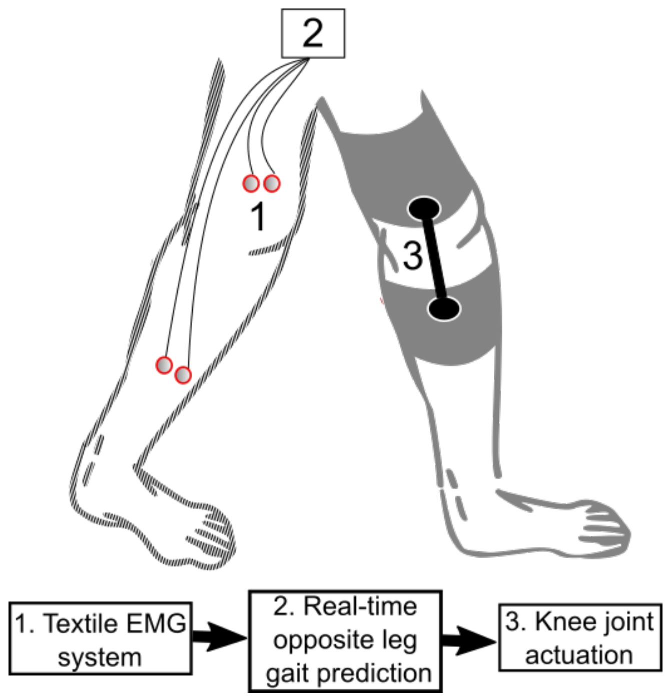

Fig. 1: Concept of the study. The use of embroidered electrode on the healthy leg for the actuation of a KAFO supporting the disabled leg is presented.

A key cost in the creation of electromechanical KAFOs is their sensorisation for purposes of automatic control. Typically, such devices use either inertial measurement units (IMUs) [6] or surface electromyography (SEMG) [7] to detect gait events such as heel-strike and toe-off, in order to determine the appropriate control mode of the KAFO. SEMG is particularly promising as a low-cost sensing modality, since it has been shown to be effective as a means to control KAFOs by decoding the muscle activity of the healthy leg [8], however, for widespread deployment the purchase and maintenance costs must be reduced.

Currently, several SEMG systems are commercially available at different price points. Non-gelled, reusable Ag/AgCl are available at approximately £11 per unit. Disposable, adhesive, pre-gelled electrodes (*e.g.,* Ag/AgCl Covidien Kendall disposable electrodes [9]) are also available, at the much cheaper price of approximately £0.26 per unit. However, the use of disposable electrodes requires users to have a stable supply of them for daily reattachment to the limb, something that is often costly and difficult to maintain in developing economies.

In contrast, recent research into smart textiles has resulted in a more affordable alternative to these traditional SEMG systems. Specifically, the use of conductive yarns embroidered onto a fabric substrate has been seen to be effective in creating low-cost, flexible and reusable electrodes, suitable for SEMG [10]. These systems are considerably cheaper than conventional systems: the cost in raw materials of a single electrode is around $£0.16$, and the fact that the electrodes are reusable drives the cost even lower. However, while they have been shown to be effective in applications involving affordable upper-limb prosthetics [11], their use in orthotics is so far untested.

In this study, the use of embroidered textile SEMG sensors is investigated with a view to assessing their suitability as the myoelectric interface of a KAFO for control of the knee joint (see Fig. 1). Experiments are reported for $N = 3$ healthy subjects, in which the performance of (i) textile-based, and (ii) conventional gel-based SEMG systems are assessed for decoding patterns of muscle activation corresponding to salient events in the gait cycle (heel-strike (HS), toe-off (TO) and rest of gait (RG)) during normal walking. Secondly, the possibility to predict gait events of one leg with *SEMG data collected from the other leg* is explored. Statistical classification is applied to perform the detection of heel-strike and toe-off and the decoding accuracy measured. The results indicate that, in this population, there is no significant difference in performance between the different electrode types with overall approximately 12% difference of accuracy in gait event detection, suggesting the feasibility of textile sensors as an alternative control interface for affordable smart KAFOs.

II. Background

A. KAFOs for Polio patients

KAFOs are long-term assistive devices to augment the functionality of multiple lower-limb segments. The reasons for prescribing KAFOs are heterogeneous, and they are commonly used to assist abnormal walking gaits, specifically abnormalities in the control of the knee and ankle joints. The etiologies of conditions that require a KAFO can include traumatic injury, neural damage such as spinal cord injury or multiple sclerosis, or muscle weakening diseases such as poliomyelitis (polio) [12].

Polio survivors in particular often require the use of orthotic devices to counteract muscle weakness. These devices are the key assistive technology for improving quality of life because it allow users to live independently [13], and increase their, and their dependents', economic well-being [14]. While polio vaccinations have reduced the number of new cases to less than 100 globally in 2018 [15], the life-long effects on the approximately $15-20$ million global polio survivors [16] remains prevalent. Additionally, symptoms do not remain stable, a revival of symptoms known as post-polio syndrome can affect up to $20-30\%$ of survivors [17] $15-40$ years after initial contraction [18].

Research and development into assistive technologies for maintaining a person's quality of life, have resulted in a vast variety of devices to counter gait abnormalities. Generally, KAFOs can be classified into three main groups [19]: 1) Passive-KAFOs: where an orthotic knee joint remains locked during ambulation, and unlocked manually for sitting. 2) Stance-control-KAFOs: where the knee joint is locked only during the weight bearing phase of gait via a passive-mechanism and knee flexion happens during the swing phase. 3) Dynamic-KAFOs: where actuation mechanisms such as springs or motors are used to control joint motion in response to sensed stages in the gait cycle. Common commercial devices include the FreeWalk from Ottobock [20], the Stride from Becker Orthopedic [21] and the C-Brace from Ottobock [22]. These devices use joint kinematics and kinetics information to provide support in stance phase and to allow free knee motion in swing. Such control presents a big improvement over a permanently locked joint that disrupts the fluidity and biomechanics of normal walking [5].

However, while these technologies are readily available in developed countries, countries which have the largest population with polio afflictions (e.g. Nigeria, Pakistan, India [15], [23]), are also amongst those with the largest socioeconomic inequalities in terms of access to healthcare. Additionally, these countries also have the youngest populations of polio survivors [24] due to global vaccination programs in 1988 to eradicate the virus. The fact that the demographic has a large young percentage is worrying, as not only is the economic power for the next generation limited, but as this demographic reaches middle and old age, an increase in individuals with post-polio syndrome will place additional demands on healthcare institutions [16]. As such, the demand for orthotic devices may increase in coming years, both in terms of first devices for patients whose condition was not previously severe enough to require one, and for patients who require more complex orthotics to handle changes in the pathology.

B. Low-cost EMG controlled KAFOs

Low-cost orthotic devices are required to enable the poorest population with lower limb disabilities to perform everyday ADLs. As such, passive-KAFOs are most commonly used, as these are the least expensive due to their simple design. However, users often experience difficulty in using the KAFO reliably in everyday situations, for example, operating the mechanism in a crowded location [13]. To solve these issues, dynamic-KAFOs allow for automatic locking and unlocking of the knee joint. The SEMG-driven solutions in particular are well suited to low-cost human motion analysis systems because it doesn't require high-end electrical engineering to be built.

The use of SEMG of the healthy leg to control an assistive device that supports the other affected leg has been explored [8]. However, nobody has explored the possibility of controlling an orthosis supporting an affected leg with SEMG data from it's healthy counterpart. With prior knowledge that normal gait (*i.e.,* walking in a straight direction) is cyclic with a specific muscle activity pattern [25], there is a potential of decoding SEMG signals from a healthy leg to control the knee joint of a passive-KAFO affixed to the affected leg in order to allow for knee flexion during the swing phase and locked knee during the stance phase using low-cost sensors.

This solution is of interest especially for polio patients, who cannot use the muscles of their disabled leg.

Recently, advances in the creation of *embroidered electrodes* [10] have resulted in a low-cost SEMG sensing system, which can be used to perform motion classification from wearables [26] or predict gestures of *phantom-limb* with amputees [11]. These electrodes can be made from inexpensive conductive textiles, and provide many advantages over standard gel or metal plate electrodes, such as re-usability and local manufacturing. Also, as they can be directly sewn into clothing at the locations necessary for measuring the muscles targeted, the need for a professional who is trained in sensor placement is reduced. These factors suggest that the use of these new sensors could be a promising route to driving down costs and thereby increasing access to smart KAFOs in the developing world with textile SEMG. However, their applicability in gait event prediction has not previously been researched, and there is no proof that the embroidered electrodes will result in similar performance compared to standard gel-based electrodes.

III. Materials and Methods

This paper reports an investigation on the feasibility of using surface electromyography data collected on the lower-limb with embroidered electrodes for the prediction of two main events of gait through classification of muscle patterns: heel-strike (HS) and toe-off (TO).[1]

A. Experimental Setup

The experimental setup and protocols for collecting data are as follows.

1) Motion capture system: The motion capture system is a Phasespace Impulse X2 with 8 cameras and a total of 13 active LED markers are used [27]. The data is collected at the rate of 120 frames per seconds.

2) Textile electromyography acquisition system: The experiments reported here use textile surface electromyography sensors developed at the the Centre for Robotics Research (CORE) at Kings College London. Four pairs of electrodes created using a Pfaff Creative 3.0 (Pfaff, Kaiser-sleutern Germany) programmable sewing machine are used, employing the design created in [28]. This design is chosen as it has been shown to have an optimal trade-off between the electrical properties of the electrodes and their manufacturability. The CAD design for the electrodes is converted to an embroidery file in the 6D Embroidery Software (provided by the sewing machine manufacturer) and stainless-steel conductive threads (Sparkfun DEV-11791, $3.28\,\Omega m^{-}1$) are used to sew out the design in fabric. For convenience, an ordinary haberdasher's snap fastener (Hemline H420.13.G, 13mm, gold brass rust-proof fastener) is sewn to the top side of the electrode to make the connection to a data acquisition device. An example electrode is shown in Fig. 2.

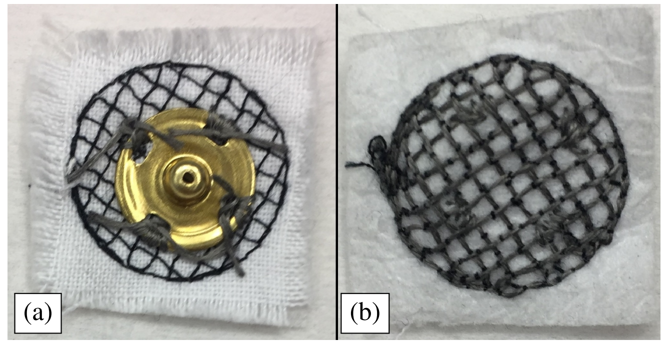

Fig. 2: Top (a) and back (b) of one of the embroidered textile electrodes used in this study. The back side, consisting of the conductive stainless-steel bottom thread goes against the skin during electromyography recording.

For future signal processing (*i.e.,* data segmentation), an additional pressure sensor (FlexiForce (FSR) Sensor [29]) is attached to the SEMG data acquisition device in order to detect when the heel of the leg where electromyography data is collected, hits the floor.

For data acquisition, the *BiTalino (r)evolution Plugged Kit BT* is used to sample data from five channels synchronously at a rate of $1\,kHz$ via Bluetooth (four channels for SEMG recoding and one channel for the pressure sensor). During data acquisition, signals are monitored by the experimenter to verify good contact with the skin (poor contact is indicated by high-amplitude noise) using the OpenSignal software package (v.2017[2]) to plot the time-dependent signal in real-time. A synthetic kinesiology tape[3] and a velcro band are used to affix the electrodes and pressure sensor at desired locations.

3) Participants and Protocol: SEMG data and kinematic data are recorded from $N = 3$ healthy male subjects with the age of 25, 24 and 28 years old.[4] The electromyography acquisition system is used to record the muscle activity from the right leg muscles and the motion capture system is used to record kinematic data from both legs. Firstly, 6 LED markers are positioned on each leg and one last marker is positioned on the sacrum according to the guidelines presented in [30]. The LEDs are placed on: the femur (greater trochanter, and lateral epicondyle),the knee (head of fibula), ankle (lateral malleolus), heel (the posterior surface of calcaneus) and toe (the head of the fifth metatarsal) of both legs. One marker is placed on the sacrum for data processing purposes [31].

The electrode placement is selected in accordance to the SENIAM recommendations [32]. A pair of electrodes are placed on the following muscle groups: the quadriceps, the hamstrings, the triceps surae and the tibialis anterior, because good gait phase classification has been obtained with this electrode location in [33]. The setup is shown in Fig. 3.

[1]The data supporting this research are openly available from King's College London at `http://doi.org/[link will be made available on acceptance]`. Further information about the data and conditions of access can be found by emailing `research.data@kcl.ac.uk`

[2]`http://bitalino.com/en/software`

[3]Note that, the tape and velcro band are used here for purposes experimental convenience. In a long-term usage scenario, positioning of the electrodes is ensured by embedding them either in a garment of clothing

[4]All experiments reported here were conducted with the approval of the Institute Ethics Committee of the Indian Institute of Technology Madras, India: IEC/2017/04/SS-1/04

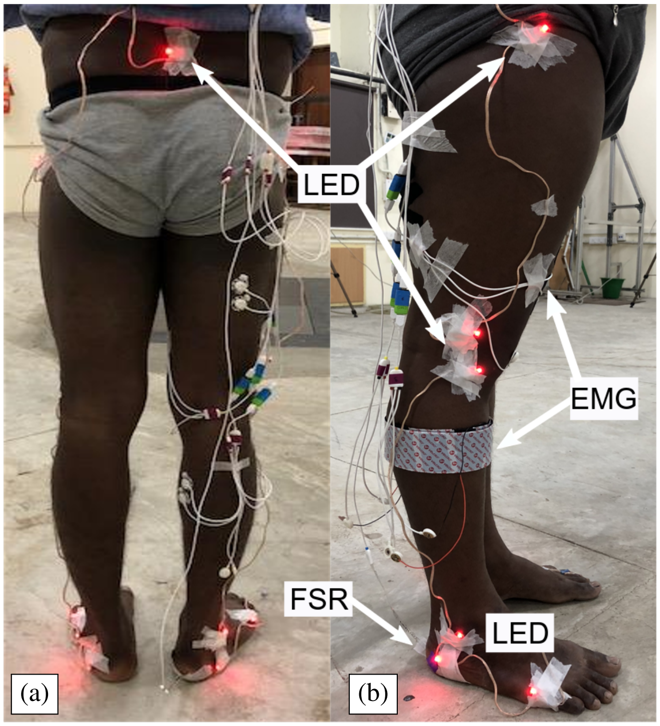

Fig. 3: Experiment setup: (a) Back and (b) side view of a participant's lower limbs with LEDs, textile electrodes and a FSR.

A trial consists of overground walking in a straight direction within the range of the 8 cameras used for motion capture (for a distance of 4 meters), while data is recorded through the motion capture and electromyography acquisition devices. Participants are asked to walk at their self selected walking speed, starting by a first step with the right leg. Before starting the experiments, a mock trial is performed to make sure that the electrodes have a good contact with the skin and the LED markers are detected by the cameras. Both data acquisitions are independent and during all trials the motion capture system starts to record before the electromyography data acquisition system. For each participant, 5 trials are performed for each electrode type: the textile electrodes and the gel electrodes.

B. Data Post-processing and Classification

To evaluate the potential of the textile electromyography system as a smart KAFO control interface, the data need to be decoded to predict key events of gait, here the heel-strike (HS) and toe-off (TO), from the rest of the gait (RG). This involves (i) the segmentation of the SEMG data, (ii) the computation of segment-wise features, and (iii) the classification of the gait events through a pattern recognition algorithm. The following describes these post-processing steps in detail. The gaps in motion capture data due to LED obstruction during the gait have been filled using the interpolation algorithm in [34] because it has good performance and the data matches with requirements (*i.e.,* straight line walk with 6 markers per legs).

1) Signal segmentation: The first post-processing step consists of segmenting the raw SEMG signal preceding the events of HS and TO. Then the data corresponding to the rest of the gait (RG) is taken aside to be counted as a third class in the classification process. In this study, the SEMG data taken from the right leg is used first to predict the event of the right leg. In the second phase, the SEMG data of the right leg is used to detect gait events of the left leg. So the SEMG data is segmented in a first place depending on gait events detected on the right leg, and then the SEMG data is segmented depending on gait events detected on the left leg.

The event of HS of the right leg is already indicated in the SEMG data through the pressure sensor input (*i.e.,* at the moment the data output is superior to 0), so the motion capture data is needed to find the event of TO of the right leg, and the event of HS and TO of the left leg, in the SEMG data. In order to find these events on the SEMG data, the motion capture data is used to (i) find Δ_{rHSTO}, (ii) find Δ_{lHSTO}, and (iii) find Δ_{rHSlHS}. Δ_{rHSTO} is the time difference between the event of HS and the following TO of the right leg in second, Δ_{lHSTO} is the time difference between the event of HS and the following TO of the left leg in second, and Δ_{rHSlHS} is the time difference between the event of HS with the right leg and the previous HS with the left leg in second. The event of HS and TO for both legs are detected in the motion capture data using the equations presented in [31], such as:

$$t_{HS} = (X_{heel} - X_{sacrum})_{max}, t_{TO} = (X_{toe} - X_{sacrum})_{min} \quad (1)$$

which represents the time at which there is a maximal displacement of the heel and toe from the sacrum marker. After detection of the event of HS and TO in the motion capture data, the previously described Δ_{rHSTO}, Δ_{lHSTO} and Δ_{rHSlHS} can be computed as a simple time difference.

After that, the event of HS and TO of the right leg and left leg are found on the SEMG data such as:

$$T_{RTO} = T_{RHS} + \Delta_{rHSTO} \quad (2)$$

$$T_{LHS} = T_{RHS} + \Delta_{rHSlHS} \quad (3)$$

$$T_{LTO} = T_{LHS} + \Delta_{lHSTO} \quad (4)$$

where T_{RHS} is the time of the event of HS of the right leg in the SEMG data in second, detected with the pressure sensor. T_{RTO} is the time of the event of TO of the right leg in the SEMG data in second. T_{LHS} is the time of the event of HS of the left leg in the SEMG data in second. $T_{LTO}$is the time the time of the event of HS of the left leg in the SEMG data in second. The first and last HS and TO are discarded for classification because it represents the initiation and end of the gait and are not in the framework of normal gait event detection [31].

Once the events are detected in the SEMG data, a segment of the length of $200ms$ is taken before the events of HS and TO detected in each trial. The rest of the data, RG, is then extracted and partitioned into segments of the length of $200ms$. The whole process is summarised in Fig. 4.

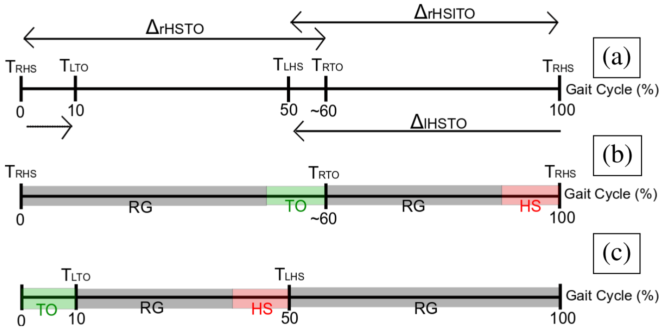

Fig. 4: Diagram showing the steps of the segmentation presented in this study: (a) shows the computation of Δ_{rHSTO}, Δ_{lHSTO} and Δ_{rHSlHS}, (b) illustrates the segmentation of the right leg data for the right leg, (c) illustrates the segmentation of the right leg data for the collateral leg.

2) Feature Selection and Classification: Once segmentation is complete, the event prediction is decoded through a statistical pattern recognition approach based on features computed segment-wise from the data. Specifically, in this paper, a one-versus-one multi-class Support Vector Machine (SVM) with a Gaussian kernel is used for classification[35].

Classification speed and performance generally depends on selecting appropriate data features as inputs to the classifier. The waveform length and standard deviation of each segment is used because good accuracy in gait phase classification have been obtained with identical time dependent features in [33].

To train the SVM, first, a 10-fold cross-validation is performed to find the optimal hyper-parameters (*box-constraint* and *kernel scale*) with respect to the accuracy

$$E = \frac{(|T_+| + |T_-|)}{|T_+| + |T_-| + |F_+| + |F_-|} \quad (5)$$

where $|T_+|$ (respectively, $|T_-|$) is the number of true positives (negatives) and $|F_+|$ (respectively, $|F_-|$) is the number of false positives (negatives).

After the hyperparameters are set, the classifier is trained on a random 70% of the feature vectors, with the remainder held back for testing. This procedure is repeated ten times for each data set (*i.e.,* for each electrode type and for each subject) and the gait event recognition accuracy is computed each time according to (5).

IV. Results

A. Gait events Recognition with Embroidered Electrodes

1) Right leg event prediction: The classification results for the embroidered and gel-based electrodes for the right leg event prediction are summarised in Table I. The detection of HS and TO using the textile electrodes reaches a maximum accuracy of 86.78% for S4. In comparison to the textile electrodes, conventional gel electrodes achieve a higher accuracy (Table I, right column) with S4 and S5, with the difference being most noticeable in S5. This difference might be due to the fact that textile electrodes have not been able to collect as much information as the gel electrodes because this participant had very hairy legs which may not have allowed the electrode to lay completely on his skin. Overall, event detection was better with S4 probably because this participant had more developed muscle than the others. An outstanding result can be seen with S3 that presents better accuracy with textile electrodes than with gel electrode. This shows that it is possible to use textile electrodes in the application of event prediction of leg where data is collected with nearly similar performances as gel-electrodes.

TABLE I: Percentage recognition accuracy in classifying the event of heel-strike and toe-off of the right leg from electromyography data from the experimental subjects. Results are mean±s.d. over 5 trials.

Subject	Textile Electrodes	Gel Electrodes
S3	83.33 ± 5.21	72.00 ± 3.77
S4	86.78 ± 3.78	93.21 ± 4.81
S5	69.00 ± 6.99	90.86 ± 3.20

2) Contralateral leg event prediction: The classification results for the embroidered and gel-based electrodes for the left leg event prediction are summarised in Table II. With the embroidered electrodes, the highest gait event classification accuracy is 76.55%. In general the textile electrodes have a lower performance than the gel electrodes. The lowest results are shown with S3 mainly due to a low development of his legs' muscles, so the event of HS and TO of the left leg are located where the difference in SEMG data with the rest of the gait data is not significant. Also, it is probable that the additional noise in the signal due to motion artifacts have lowered the performances in event prediction with embroidered electrodes. S4 and S5 again present the best results with gel electrodes (*i.e.,* $93.20 \pm 3.20\%$ and 87.40 ± 6.33) because they are more conductive and allow for collecting more information in the data. The results show that contralateral leg event prediction is possible, and embroidered electrodes have performances slightly lower than gel electrode for this application.

TABLE II: Percentage recognition accuracy in classifying the event of heel-strike and toe-off of the left leg from electromyography data from the experimental subjects. Results are mean±s.d. over 5 trials.

Subject	Textile Electrodes	Gel Electrodes
S3	65.51 ± 0.00	66.66 ± 0.00
S4	76.55 ± 3.82	87.40 ± 6.33
S5	76.00 ± 6.52	93.20 ± 5.35

B. Classifier Evaluation

To investigate why the classifier performance is lower for the contralateral leg event prediction with textile electrodes, the within-classes accuracy (*i.e.,* the performance of the classifier in distinguishing *between* HS, TO and RG) is presented in Fig. 5 for the participant S4.[5] It can be seen that

[5]The diagonal of the *confusion matrix* indicates the positive predictive rates (*i.e.,* $r_+ = |T_+|/(|T_+| + |F_+|)$), meaning that it represents the proportion of feature vectors that are classified correctly. The other cells of the matrix indicate false discovery rates (*i.e.,* $r_- = |F_+|/(|T_+| + |F_+|)$) representing the rate of feature vectors that are misclassified as another gait event.

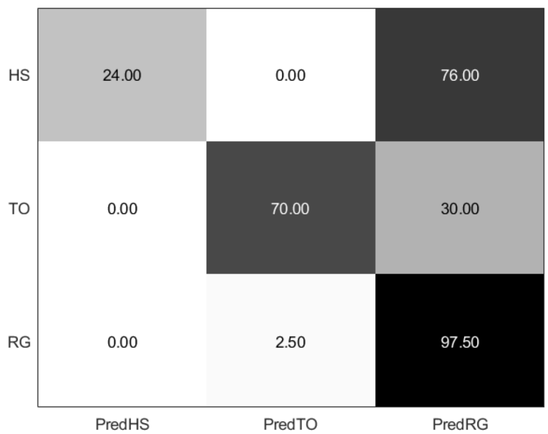

Fig. 5: Within-classes recognition rate of contralateral gait event prediction for S4 with textile electrodes.

the error comes from the fact that HS and TO are predicted as RG Ṫhis error is more present in the prediction of HS than TO. It means that the information taken prior to the event of HS and TO have been similar to the information used to train the RG class. The reason for this error is because the number of feature vector used to train the classifier is lower for HS and TO than RG. This error is consistent for classification accuracies below 80%. However, it is expected that this error decrease when balancing the dataset.

V. Discussion

In this paper, the application of embroidered textile electrodes in detecting heel-strike and toe-off events during normal gait with a view for future control of the knee joint of a KAFOs is presented. A difficulty in myoelectric control is the user reliance on disposable, gel-based electrodes for controlling the orthosis. This paper proposes the use of embroidered electrodes for muscle activity monitoring as a low-cost alternative, with the benefit of reusability and local manufacturing. To evaluate the proposed approach, SEMG data collected on the right leg is used to predict the HS and TO event of the same leg, and then the same data is used to predict the HS and TO event of the left leg (*i.e.,* the contralateral leg). The experiments performed in India show that there is a potential to predict gait events with gel electrodes and with textile electrodes, albeit with a comparatively decreased performance. However, a daily use of electrodes in the extreme living condition such as hot weather is still not viable for gel electrodes. The textile electrodes could be a viable solution as perspiration due to the hot weather could increase the conductivity of the interface and allow for more sensitivity to muscle activation signal. Future studies have to be performed outside of the laboratory to assess the performance of the textile electrodes in extreme conditions. The robustness of the textile electrodes during daily use will be investigated, to evaluate the performance of the electrodes under conditions such as changes in temperature, humidity (and associated perspiration) or electrode displacement due to movement.

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